CHAPTER-12

DIGITAL TRANSFORMATION IN HORTICULTURE: A REVIEW OF INTEGRATION OF AGRICULTURE 4.0 TECHNOLOGIES FOR SUSTAINABLE FOOD SYSTEMS

Divya Jaiswal[1]
[1]Somaiya School of Humanities and Social Sciences, Somaiya Vidyavihar University, Mumbai, Maharashtra, India
Corresponding author: divyajaiswal0903@gmail.com

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Abstract

The Food and Agriculture Organization (FAO) warns of impending food security as the global population nears 10 billion. This poses a significant challenge to horticulture sector where one third of the produce is lost or wasted. This review explores the transformative potential of Agriculture 4.0 technologies, mainly artificial intelligence, Internet of Things, blockchain and robots and devices, in enhancing food security and creating sustainable supply chains. These technologies can help in early disease detection, pest management, efficient resource use, improving yield and enhancing post-harvest management. Further it can help to manage inventory efficiently and ensure quality control and transparency in the supply chain. But adoption of these technologies is faced by barriers of infrastructural gaps, lack of technical knowledge, and financial hurdles. Wider adoption requires improved digital infrastructure, financial support systems, localized AI solutions, farmer training programs, and stronger public–private partnerships.

Keywords: Agriculture 4.0, Artificial Intelligence, Internet of Things, blockchain, horticulture, technology adoption

1. Introduction

As the global population is projected to reach between 9 and 10 billion people by the year 2050 as per United Nations Food and Agriculture organization (2025), the global food production must increase by 50% compared to 2012 levels to ensure food security and eradicate hunger. Yet in many areas' agriculture is seeing diminishing productivity due to issues like water scarcity, soil degradation and natural calamities (Stern, 2026). A shift from traditional to modern methods of agriculture is needed to meet the future demand. In this context it is important to study the application of AI in agricultural systems to enhance long term productivity and sustainability.

This inclusion of AI in agriculture is seen as the fourth revolution in agriculture, also termed as "Agriculture 4.0" (Stern, 2026). It involves integration of AI, Internet of Things (IoT) devices, blockchain, machine learning etc. into the entire food supply chain. Stern explained it as leveraging high volume data collections, sensors, and predictive analytics to grow more food with less labour, water, and land. AI not only optimises processes like harvesting but also helps to decide which fertiliser to use based on soil and crop data (Adelina et al., 2025). It also predicts weather changes and any pest infestation in crops and helps to optimise logistics.

For horticulture products, supply chain is major sector for innovations, as these products face he constraint of shorter shelf life. The Food and Agriculture Organization (FAO) (2025) estimates that approximately one-third of all food produced for human consumption is lost or wasted annually (Adediran et al., 2025). These losses occur at every stage, from harvesting and storage to transportation and retail, significantly impacting economic stability and environmental sustainability. Traditional supply chain management (SCM) often fail to address these due to lack of transparency, and limited response to changing market dynamics (Kumar, 2025). Integration of AI, blockchain and IoT can help create a robust system, offering solution to these issues, using analytical capabilities and real time data.

However widespread adoption of these technologies faces several economic, social and technological challenges. High cost can be a deterrent from adoption of AI in agriculture in developing countries and by small farmers (Adediran et al., 2025). Deployment is further hampered by a lack of technical expertise and infrastructure constraints. Concerns over cyber security and data privacy also play a role (Stern, 2026). The quality of data may also impact the kind of solutions offered by these innovations.

This review paper explores the potential of Agriculture 4.0 technologies in horticulture. This study identifies key application areas of AI and other technologies and the determinants of technology adoption. This research highlights the limitations and suggests solutions.

2. Literature Review

Technologies of Agriculture 4.0

Agriculture 4.0 involves integration of traditional farm practices with advanced technologies to create a robust farming system that has high productivity and is sustainable (Stern, 2026). It involves using Artificial intelligence (AI) and its subsets, i.e. machine learning (ML) and deep learning (DL). The high analytical capabilities can be leveraged to predict yields and forecast weather accurately and help in problem solving ((Ayed & Hanana, 2021; Adelina et al., 2025). Various DL models are used in agricultural applications. ANN (Artificial Neural Networks) are used for agricultural automation, CNN (Convolutional Neural Networks) help in image-based tasks like disease detection and yield estimation (Chaudhary et al., 2025).

These analytical tools are supported by Internet of Things (IoT). It is a network of linked devices that help to collect data. It helps in real time monitoring of factors like soil moisture, temperature, humidity etc. IT is used for inventory management, and monitoring weather and plant growth, optimising yields (Kumar, 2025; Busran et al., 2025).

This system is further enhanced by Blockchain technology, which acts as a decentralised, tamperproof record of transactions and product movements from farm to consumers- reducing frauds and ensuring food safety (Kumar, 2025). It thus ensures data interest, transparency and increases tractability across supply chain. It also helps to improve efficiency, increase operation speed of supply chain and expiate verification process.

Finally, robotics and unmanned aerial vehicles equipped (UAV) with AI powered sensors and cameras automate labour intensive tasks like harvesting, large scale crop health monitoring and precision spraying (Chaudhary et al., 2025).

Guo et al. (2026) have shed light on the emerging Scientific Machine Learning (SciML) framework, that bridges gap between data driven neural networks and kinetic models, to improve predictions even with limited data, by “incorporation of knowledge-based rules to guide learning process”. More research is needed to standardise its application.

Combined application of these technologies can help form a robust system for supply chain management. While IoT can collect necessary data, AI can analyse it to provide valuable predictions and solutions blockchain will add a layer of transparency and tractability, ensuring integrity of data. The AI based robots and UMV.s will help automate processes and improve efficiency. Researchers (Huang et al., 2025) mention the Edge-Cloud-Blockchain-Terminal (ECBT) framework, which represents this integration, where blockchain forms the core, linking heterogeneous components, creating unalterable audit trails.

3. Application Domains in Horticulture

Highly perishable nature of horticultural produce adds complexity its supply chain. It necessitates high precision supply chain management to minimise waste. This can be achieved using the various technologies of Agriculture 4.0.

Disease and pest management

AI driven UAV's utilising CNNs are used to analyse and detect pest and diseases. Saxena et al. (2026) found these technologies to be 85-90% accurate in detecting pests and diseases in temperate Himalayan crops (p.4). This allows for early diagnosis and enables targeted treatment, thus reducing use of pesticides, bringing down costs and environmental impact (Singh et al., 2022; Sharma et al., 2025). Further, the insights by AI can help horticulturalists to develop new, disease resistant varieties, through identification of genetic traits (p.3).

Resource management

Technology integration can help optimise resource use through site-specific feedback. Integration of AI and IoT can help in effective nutrient management and irrigation. The real time data on weather and soil moisture is used by AI for making efficient irrigation schedules. These have been effective in reduction of water usage in water scarce regions by 40% (Bhat et al., 2025). Similarly, multispectral mapping can help identify nutrient deficiencies, allowing for precise fertilizer application (Saxena, et al., 2026). This paves way for sustainable horticulture- by saving water and reducing use of fertilizers.

Yield and Quality Predictions-

ML based models help in prediction of ripening of fruit and thus determine the optimum harvest time. DL based models are used for fruit detection, counting systems and yield predictions (Chaudhary et al., 2025; Saxena et al., 2026). Quality assessment and categorisation of horticultural products is important for pricing and marketability. AI based models have been developed to predict sugar content, moisture levels and firmness in fruits like oranges and melons (Guo et al., 2026). Machine vision systems combined with ML algorithms analyse fruit colour, texture, size, and shape to classify produce into quality categories (Chaudhary et al., 2025). Applications include grading bananas, detecting defective tomatoes, segmenting decay zones in stored apples, and identifying citrus fruits in orchards. Beyond this, AI technologies are increasingly integrated into smart agriculture systems, including hydroponic tomato production and intelligent greenhouse management, where sensors and ML optimize resource use, climate control and crop management to enhance both yield and quality.

Post-harvest management

Post-harvest management is essential to control food loss and wastage. AI and IoT integrated systems are used to detect contamination, spoilage and decay early, before products move along supply chain (Adediran et al., 2025). Machine learning algorithms analyse large datasets to predict factors such as demand variations, spoilage rates, and optimal storage conditions, enabling suppliers and retailers to make better decisions that minimize waste. AI can be used to monitor and control the environment in storage facilities, thus extending shelf life. Further, predictive models can be used for predictive models can suggest modifications to transportation routes to prevent spoilage during transit (Adediran et al., 2025) (Saxena et al., 2026).

Retail and inventory management

According to Adediran et al. (2025) AI based prediction systems can help enhance inventory management, by optimising restocking schedules and demand forecasting, minimising overstocking and understocking, thus reducing wastage. AI based techniques have also been used to analyse consumer behaviour and preferences, helping retailers to understand market demand and optimise business decisions (Chaudhary et al., 2025). Blockchain based integrated systems help to track products in agriculture market. This helps to improve food safety and provide quality assurance- which is increasingly demanded by consumers recently.

4. Determinants and Barriers to Adoption

The adoption of AI in agriculture and horticulture is influenced by various factors. Sood et al. (2024) have classified these factors into 5 main categories- individual, environmental, technological, demographic and structural factors. Individual characteristics of users, like performance expectancy, ease of use and risk aversion determines the adoption of AI. The more efficient and easier to use the technology is perceived to be the more it is adopted. Risk aversion also plays a significant role, as many farmers remain cautious about adopting unfamiliar technologies due to concerns about unreliable recommendations, weather predictions, or financial uncertainty.

Technical infrastructure, support and technological readiness influence farmer's willingness to adopt digital tools. Access to training programmes increases readiness to adopt AI systems. Social influence, i.e. recommendations by peers and community members, impacts adoption of new technology. Availability and access to information also impacts use of AI tools. But lack of necessary infrastructure, like reliable internet connectivity, stable power supply- often hinders its adoption, especially in rural areas and emerging economies (Adediran et al., 2025). Also lack of technical expertise in farmers hinders adoption of AI (Ayed & Hanana, 2021).

Concerns regarding data security and privacy remain important barriers. Farmers are often cautious about sharing farm-related data and require assurance regarding transparency, safe data handling, and informed consent (Sood et al., 2024).

Financial condition is also a major factor. Adoption is often hindered by the high cost of these technologies. Only farmers with strong financial capabilities readily adopt AI based technologies. This this also presents as a major constraint in widespread adoption of agriculture 4.0 technologies (Liao et al., 2026).

Structural factors like farm size also impacts adoption. Large farm sizes are often positively correlated with earlier adoption (Sood et al., 2024). Conversely, the fragmented landholdings typical of mountainous regions like the Himalayas limit the scalability of many "smart" systems (Saxena et al., 2026).

Lastly, demographic factors also shape farmers' willingness to adopt AI technologies. Younger farmers show greater openness to innovation and have higher risk-taking ability as compared to older farmers. Education also impacts adoption of AI, as it can improve technical understanding and confidence in using advanced technologies (Chaudhary et al., 2026; Sood et al., 2024).

5. Methodology

Various research articles have been reviewed from databases and journals like ScienceDirect, EBSCO, Directory of Open Access Journals etc. Papers published in past 5 years (2021-2026) related to Agriculture 4.0 technologies application and use in agriculture have been reviewed in this article. In the present study, 20 articles were selected from the mentioned sources. These articles were then reviewed via narrative analysis.

6. Results

Adoption of these technologies have shown positive results. AI driven application has shown improvement in crop yield by 12-25%, leading to increase in income by 15-20% (Olutumise, 2026). Bhat et al. (2025). have mentioned about application of AI powered decision support system in Andhra Pradesh, giving 30% increase in crop yields, and 20- 30% rise in net incomes (2025). Gupta et al. (2026) found that use of AI monitoring systems in chilli farming case study in India increased per acre yield by 21% (2026). Use of AI in vineyard management in a pilot study in California showed 25% rise in grape output.

AI integrated systems have found to reduce nitrogen fertilizer use by 25% and have reported improvement of 15-20% in efficiency of resource use (Olutumise, 2026; Saxena, et al., 2026). Use of AI mapping in India documented decrease in expenditure on fertilizer and pesticide by 15% and 19% respectively (Jayadatta, 2024; Saxena et al., 2026) have found these technologies to reduce water usage by 30-50% in Himalayan region.

AI integrated technologies have shown remarkable results in pest management. Saxena et al. (2026) have found it to be 85-95% accurate in pest and disease detection in Himalayan crops. Article by Chandra et al. (2025), mentioned about a deep convolutional neural network (CNN) based algorithm being 99% successful in classifying and identifying potato diseases. Chaudhary et al. (2025) have found in their research about an AI based model that detects diseases in papaya with 70% accuracy. They have also mentioned about MobiNetV2 model, which classifies diseases in citrus plants with an accuracy of 97%. (Wieme et al., 2022) found hyperspectral imaging technology successful in detection of fungal infections in vegetables with an accuracy ranging 89-96% for squash and 90% for tomato. They have found these technologies to be useful in early detection of bacterial and fungal diseases in mushrooms, with 75% accuracy in classification of fungal infections. The system was even able to distinguish between browning of mushrooms due to physical damage and bacterial infections with accuracy of 95%.

AI based systems have also been successful in sorting horticultural produce into different grades with accuracy of 90% (Saxena et al., 2026). Integrated technologies have been very useful in classification of the produce on basis of ripeness, firmness, water content, acidity etc. Hyperspectral imaging-based systems successfully detect ripeness on basis of pigment detection with high accuracy (80-90%) and classify the fruit/ vegetable on basis of level of maturity (Wieme et al., 2022). It can also help detect damage during post-harvest handling like freezing. The system was able to separate chill damaged peaches with an accuracy of 95% and cucumbers with 91% accuracy. AI based supply chain optimization models have been found to reduce post-harvest losses by 15-20% (Gupta, et al., 2026). Price forecasting AI models have helped farmers in strategic sales for tomatoes and onions, increasing profits by 12% (Olutumise, 2026).

7. Suggestions

To bridge gap between technological potential and farm level adoption, following solutions were suggested by researchers. Development of localised AI systems can ensure greater effectiveness. This should be done in collaboration with the local stakeholders and experts, to improve cultural and contextual suitability of these technologies (Bhat et al., 2025). Infrastructure development by expanding digital infrastructure in rural areas can help for their wider adoption. Development of solar powered models can also be a sustainable solution for technological introduction in rural areas (Huang et al., 2025).

Micropayment mechanisms and be made, and subsidies provided for initial deployment can help reduce financial burden on small farmers, thus improving accessibility and affordability (Huang, et al. 2025).

Organising training programmes which are region based and in local language can help improve AI literacy and technical skills among farmers, encouraging wider adoption (Bhat et al., 2025). Public private partnerships can help implementing AI powered systems in resource scare regions.

The Government of India has already taken certain initiatives towards integration of these innovative technologies in the Indian agricultural scenario. GoI launched Digital Agriculture Mission in 2024. The Mission aims to provide all farmers with timely access to accurate and reliable crop-related information by utilizing authenticated data on farmers, landholdings, and crops, along with advanced digital technologies (PIB, 2026).

8. Future Scope

AI can help transform horticulture at various fronts, but its potential can be realised after crossing the technical and financial hurdles. Future research can focus on development of AI based models for specific geographical terrain and crops, for optimising the output and farmer incomes. Standardised datasets need to be built and should be made accessible to improve reliability of AI models. Better integration of AI in vertical farming and scaling up these in urban areas can help address growing pressure of food security and improve nutrition. Also, research is needed to realise the socio- economic impact of adoption of these technologies in India.

9. Conclusion

Integration of Agriculture 4.0 technologies has potential to transform horticulture in to more sustainable efficient and resilient sector. The combined use of artificial intelligence (AI) machine learning (ML), Internet of Things (IoT), blockchain, robotics and unmanned aerial vehicles can significantly increase efficiency of horticulture, right from the farm through end of its supply chain. These technologies can help improve resource management thus providing a solution to meet future demand sustainably. It also provides a mechanism for early disease and pest detection, which can be helpful in taking targeted action at right time, reducing pesticide consumption. Thus, in horticulture using these technologies can help reduce negative externalities resulting from farm activities.

These technologies can predict yield and do quality assessment, helping in the tedious task of quality control. It also optimises inventory management and helps in effective postharvest handling- thus reducing food waste. Lastly, as these technologies keep immutable records, it can help bring transparency to the consumers, who may want to know the origin of the products.

Despite these benefits the widespread adoption of these technologies in horticulture remains limited. Farm size, social influences, technological readiness and financial capability strongly impact adoption of these technologies. Infrastructural gaps, lack of technical expertise, high implementation costs and concerns related to data privacy act as a barrier to its wider adoption, especially in developing regions and among small farmers.

Successful implementation requires development of digital infrastructure and supportive financial ecosystems. Also, development of localised AI systems, solar powered models and organising training programmes in local language and enable wider adoption in rural areas. Public private partnerships can help implementation of these technologies in resource scarce regions.

The future of sustainable horticulture depends on successful integration of advanced digital technologies and traditional agricultural practices. With proper support and inclusive strategies, wider adoption of Agriculture 4.0 technologies can help in achieving the Sustainable Development Goals (SDG's) of zero hunger and responsible consumption and production, by enhancing food security and reducing post-harvest waste.

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